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The forecasting power of real interest rate gaps: an assessment for the Euro Area

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Abstract

The real interest rate gap or IRG -the gap between the short term real interest rate and its "natural" level-, is a theoretical concept that has attracted much attention in central banks in recent years. This paper aims at clarifying its practical relevance for monetary policy in real time. For this purpose, it provides an empirical assessment of the usefulness of a semi-structural versus purely statistical estimates of the real IRG for predicting policy relevant macroeconomic variables in the euro area. However mixed, the results confirm that semi-structural estimates of the real IRG deserve being added to the central banks' toolbox.

Keywords: natural rate of interest, monetary policy, forecasting.

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1. Introduction

This study investigates the informational content of the gap between the real short term rate of interest and econometric estimates of its "natural" level -in short the real interest rate gap (IRG)- for selected, policy relevant, macroeconomic variables in the Euro area. Although there is still nothing like a consensus as to the precise definition of the natural rate of interest (NRI), it is frequently defined in practice as the (equilibrium) level of the real short term rate of interest which is consistent with output at its potential level and a stable rate of inflation in the medium term (ECB, 2004).[1] The potential policy relevance of the concept (cf. e.g. Blinder, 1998) has motivated a bunch of empirical papers presenting estimates of the natural rate of interest for the United States, the Euro area and other developed economies over the last few decades.[2] In most recent papers, the empirical strategy followed the semi-structural approach pioneered by Laubach and Williams (2003), who estimated the NRI for the USA within the framework of a simple unobservable-components macroeconomic model.[3] Although typically plagued with a large measurement uncertainty in real time, such estimates proved useful to evaluate the monetary policy stance retrospectively.

Ultimately, however, a crucial point for deciding whether or not central banks should compute and monitor on a regular basis measures of the NRI and of the corresponding real interest rate gap is the predictive power of such indicators regarding future fluctuations of policy relevant variables, like inflation or GDP growth. In a recent speech, Bundesbank President Axel Weber (2006) expresses very clearly that this should be one major concern of the monetary policy-maker in practice:

> "One can not judge the usefulness of the natural rate of interest for monetary policy purposes without taking into account the serious problems that

[1] Giammarioli and Valla (2004) provides an useful survey of competing definitions and methodological approaches.

[2] See Crespo-Cuaresma, Gnan and Ritzberger-Grünewald (2005) for a survey of this empirical literature.

accompany its measurement and estimation (…). Seen from this perspective, it may be worthwhile to examine in more details what information content the real-time estimates of the natural rate of interest from various empirical approaches –or more precisely the implied interest rate gaps- have for future inflation".

Unfortunately, available indications of an informational content of empirical interest rate gaps for policy relevant variables are exclusively based on in-sample evidence of lagged correlations and cannot settle the point raised by Prof. Weber. Indeed, in-sample regressions can only be suggestive of their leading indicator properties. Since model-based estimates of the natural rate of interest at a given time-period usually incorporates some information about the future values of the other variables that enter the model –among which inflation-, much of the exhibited in-sample cross-correlations may be spurious and in fact poorly indicative of the true informational content of the real IRG for inflation in *real* time.

In this paper, I aim to test for the practical significance of empirical real IRG estimates for the euro area in a more systematic way. For this purpose, I focus on real IRG estimates constructed via a range of statistical techniques that may be deemed reasonably easy to implement and update. I then simulate a standard out-of-sample forecasting experiment to properly investigate the leading indicator properties of these estimates for key Euro area macroeconomic variables: inflation, GDP growth, unemployment, and credit to the private sector.

It is well known by practitioners that assessments of the economic outlook or the policy stance based on *ex post* revised time-series can differ substantially from what may be inferred in real time using available data. Having access to a real-time database, which allows reproducing the situation faced by a policymaker in real time, is thus *a priori* required to assess the forecasting power of any synthetic indicator, and econometric estimates of the

[3] Recent references include Mésonnier and Renne (2006), Cour-Thimann et al. (2004), and Garnier and Wilhelmsen (2005) for the Euro area, Larsen and McKeown (2004) for the UK, Basdevant, Björksten and Karagedikli (2004) for New_Zealand, Manrique and Marquez (2004) for Germany.

IRG should not be an exception[4]. I therefore conducted this forecasting exercise using reconstructed real-time IRG series over the first seven years of the euro.

The rest of the paper is organized as follows. Section 2 deals with data issues. Section 3 presents the alternative measures of the real IRG that are implemented in the rest of the paper. Section 4 gives a preliminary assessment based on in-sample correlations with macroeconomic variables of interest. Section 5 details the methodology for the simulated out-of-sample forecasting experiments. Section 6 comments the results and provides with robustness checks. Section 7 concludes.

2. Data

This analysis uses time series reconstructed for the Euro area over the period 1979Q1-2004Q4 with quarterly frequency. The first year corresponds to the EMS entering into force. Historical series for Euro area real GDP, consumer prices (HICP) and the 3-month nominal rate of interest were taken from the second version of the ECB's AWM database (see Fagan et al., 2001) and have been updated up to the end of 2004 with the official data published by Eurostat and the ECB, as of mid-November 2005. Concretely, Eurostat official data were used over their whole period of availability (i.e. from 1991 Q1 or 1992 Q1 onward) to allow for consistency with common knowledge of the recent economic juncture. These official series were then backdated with the corresponding historical series. Whereas the national accounts series provided by the AWM database are seasonally adjusted, the historical HICP series is not and I hence preliminarily adjusted it using the Tramo/Seats procedure. The ex post real interest rate series was computed as the nominal interest rate deflated with the current annual rate of inflation.

[4] A recent paper by Clark and Kozicki (2004) illustrates this point. They build on the pioneering work of Orphanides and van Norden (2002), who provide evidence of difficulties in estimating the output gap in real time, which suggests analogous real-time difficulties in estimating the also unobservable equilibrium real interest rate. Using a range of unobserved components models and 22 years of real-time data vintages for the United States, they find that data revisions substantially contribute to imprecision in real-time estimates of the equilibrium real rate of interest, up to 100-200 basis points of revisions to less recent estimates and about 50 basis point for more recent ones.

The historical series for credit flows and outstanding amounts from euro area monetary and financial institutions to the domestic credit sector are provided by the ECB on its website and regularly updated. However, they begin in year 1983 only. Following the methodology reported by the ECB in the statistical annexes of its Monthly bulletin, I computed an index series of outstanding amounts of credit adjusted for changes that do not arise from transactions, with December 2001=100 set as the base period. I calculated then the rate of growth of nominal credit (end of period data) using the index series, that I previously adjusted for seasonal fluctuations. Real credit growth was then computed as nominal growth deflated by HICP inflation. For the sake of consistency of the definitions of growth rates, all three series for GDP, HICP and credit have been turned into logarithms.

The experiment conducted in this paper is designed to mimic in a simple way the problem facing a policy maker who wishes to forecast inflation or other macroeconomic variables in real time. This obviously requires the use of real-time dataset. Unfortunately, no such dataset is available for the Euro area yet, at least over a long enough time-span. Therefore, I reconstructed for the purpose of this study a set of monthly real-time GDP vintages for the Euro area that extends the data set currently made available by the EABCN on its website, spanning the observation period from the beginning of the euro to the end of 2005[5]. Real time releases prior to January 2001 were taken from the electronic archives of the Banque de France, and were partly completed when necessary with the information published in the first issues of the ECB's Monthly Bulletin.[6] Since the officially released series begin in 1991 at the earliest, I also used the AWM series to backdate them. Note that, in order to accommodate the break consecutive to the entry of Greece into EMU in January 2001, I used for this purpose two different vintages of the AWM GDP series, one anterior to 2001 (as in the first version of the database) and one posterior (as in the first revised version, ending in 2002Q4). Table A.1 in Appendix A provides with details of the GDP vintages that are used

[5] The Euro Area Business Cycle Network is currently developing a wide-ranging real-time database for the euro area, but real-time GDP vintages were not available before observation date 2001Q1 when this paper was written.

in this study. Following e.g. Orphanides and van Norden (2005) for the US, I otherwise assumed that inflation and unemployment rate series were little revised by statisticians, as notably seasonal adjustment procedures usually account for most of the small changes observed between successive price releases in the ECB Monthly Bulletin. Thus, I used final versions of those series, combined with the real time GDP vintages, in the out-of-sample simulations presented in section 5 below.

3. Alternative measures of the interest rate gap

Using the Kalman filter to get measures of unobservable time-varying "natural" variables like potential output, the NAIRU, or the neutral real interest rate, has become a popular empirical strategy over the recent years.[7] In most cases, this so-called "semi-structural" approach relies on a reduced-form model of the economy (a backward-looking Phillips curve and an IS curve), which helps bringing some economic structure into the definition of the unknown "natural" variables, while postulating some DGP for the unobservable variables. From the viewpoint of the policy-maker, the time-series or semi-structural approach of the NRI may arguably strike a convenient compromise between the complexity of more structural approaches, which involves the complete derivation and estimation of micro-founded DSGE model (see e.g. Neiss and Nelson, 2003 or Edge et al., 2005), and the arbitrariness of simple univariate trend extractors, such as the commonly used HP filter, whose simplicity of use may be at the cost of economic interpretation (Larsen and McKeown, 2004, Giammarioli and Valla, 2004). One objective of this study is then to check whether such a model-based approach to the NRI significantly improves upon the information content of simple detrended real interest rates.

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[6] I gratefully thank the staff of the Economic Database Management Division of the Banque de France for their kind help in retrieving these real-time vintages.

[7] For estimations of the first two variables, see e.g. Staiger, Stock and Watson, 1997, Peersman and Smets, 1999, Gerlach and Smets, 1999, Laubach, 2001, Fabiani and Mestre, 2004.

In a relatively loose way but one which is clearly reminiscent of the genuine proposal by Knut Wicksell (1898), the NRI may be defined (1) as the real rate of interest which is consistent with stable inflation in the medium term, (2) as an equilibrium real rate –one that equates savings and investment flows-, thus being positively correlated with the trend growth rate of output. Mésonnier and Renne (2006) provide with a semi-structural estimate of the NRI for the Euro area which matches both definitions, broadly following the lines of Laubach and Williams (2003) for the US economy. The resulting interest rate gap –denoted by MR in the following- is considered here along a few competing purely statistical approaches. These include ex post real interest rate series[8] that are trend-corrected using common univariate statistical filters: a quadratic trend (noted QT), the standard Hodrick-Prescott (1997) filter and a variant of the band-pass filter by Baxter and King, the Christiano-Fitzgerald (2003) asymmetric filter (noted CF below).[9] As regards the HP filter, I consider here two cases, depending on the choice of the smoothing parameter: with a smoothing parameter of 1,600 (the standard value for quarterly data) on the one hand and of 26,500 on the other hand, as recommended for instance by Orphanides and Williams (2002). These values for the smoothing parameter roughly correspond to an extraction of cycles of less than 10 and 20 years respectively (noted as HP1 and HP2 in the following).[10] For completeness, I also consider the output of a multivariate (purely) statistical filter, a version of the Harvey and Jaeger (1993) model, which has been applied recently to the issue of NRI estimation in the euro area (see Crespo-Cuaresma et al., 2004). Here, the Kalman filter is used to decompose jointly the ex post real interest rate, the (log of) real GDP and the rate of

[8] The ex post real interest rate is computed as the nominal rate deflated by annual inflation. The current annual rate of inflation (with the price level expressed in logs) is equivalent to the simple non-weighted average of the last four lags of quarterly inflation. It can then be seen as a simple way to form current expectations of next period quarterly inflation. In practice, simple estimates of the real interest rate often rely on current annual rather than quarterly inflation, the former being by construction less volatile than the latter.

[9] The CF filter approximates an optimal band-pass filter like the more common Baxter and King (1999) filter, but, in contrast to the latter, weights are asymmetric in past and future values of data and they vary over time. As a consequence, the CF filter does not lose any observations at the end of the sample. The CF filter is specified in the following so as to extract cycles of 2 to 40 quarters. Consistently with the results of unit-root tests for the real interest rate (see appendix B), the underlying series is assumed to be integrated of order one and is consequently drift corrected before the filter is applied.

[10] The relation between the cut-off frequency ν_c and the smoothing parameter λ is $\nu_c = (\pi/4)^{-1}\arcsin(2/\lambda^{1/4})$, see for instance Iacobucci and Noullez (2005).

quarterly inflation into the sum of a trend, a cycle and an irregular component. By assumption, the multivariate trend component is defined as a local linear trend, that is to say a random walk with drift where the drift itself follows a random walk, while the stochastic cyclical component is then specified as a sine-cosine wave with a dampening factor. Some more details about the estimation procedure of the MR and HJ models are presented in Appendix B.

Figure 1 shows the resulting measures of the interest rate gap, as estimated over the whole 1979Q1-2005Q3 period on the basis of revised ("final") data. At first sight, the gaps yielded by mechanical statistical filters (QT, HP, CF and HJ models) appear to be very close from one another and of limited amplitude (in a corridor between -2.0% et 2.0%). Besides, the very close fluctuations of the two HP filtered gaps suggest that most of the fluctuations in the ex post real interest rate correspond to cycles of up to 10 years (the cut-off period of the HP1 filter and of the CF model). Conversely the MR baseline IRG exhibits fluctuations that are similar in amplitude to that of the simple demeaned real interest rate over the last two and a half decades (roughly speaking from -4.0 % to +7.0%).

[insert Chart 1 about here]

Broadly speaking, all IRG indicators point to a switch from an inflation-accelerating stance (a negative IRG) in the late 1970s to a marked disinflationary policy in the early 1980s (a positive IRG), which is consistent with the common knowledge about the general shift in the monetary policy stance of most continental European countries over this period. This disinflationary stance in the Europe of the 1980s is however mostly emphasized by the MR measure. An also relatively consensual spike in the early 1990s reflects the vigorous interest rate hikes by some central banks of the former European ERM to counter the speculative attacks which led to the 1992-1993 crises, whereas most measures converge towards a diagnosis of expansionary monetary policy in 1999. However, from 2000 on, the various indicators tend to tell diverging stories. In particular, the MR and HJ Kalman filter based IRG agrees with the simple HP filtered IRG (at least up to 2004) and signals a relative return to neutrality, while a simple demeaned real interest rate would point to a considerable negative gap, which seems quite implausible considering the mixed growth and relatively subdued inflation records over the first years of the 2000 decade in the euro area. Regarding 2005, i.e. the end of the sample, the MR gap leaps more evidently into the negative territory, which would appeal for a "normalization" of the accommodative monetary policy stance, a story that one could easily reconcile with the ECB's putting an end in December 2005 to its two-years long status-quo policy and the launch of a new series of interest rate hikes from end 2005 onwards.

4. In-sample evidence on the informational content of real IRG estimates

The standard interest rate channel of the transmission mechanism of monetary policy relies on there being a link between short term real interest rates and the real side of the economy. This can be easily understood within the framework of the simple macroeconomic workhorse model, where a Philips curve combines with an IS curve to account for a transmission of monetary policy impulses first to aggregate demand and finally to inflation. The main components of aggregate expenditure which are theoretically held to be affected by changes in the short term real interest rate are then consumption, although substitution and wealth effects can work in opposite directions, and investment.[11] However, the empirical evidence on these expected links is rather mixed (see e.g. the survey in Taylor, 1999). As argued for instance by Neiss and Nelson (2003), who exhibit a surprising positive correlation between the short term real rate and detrended output in the UK over 1980-1999, the reason for this could be unacknowledged changes in the level of the "natural" rate of interest.

[11] While modern central banks have a direct command of the short term nominal interest rate only, monetary policy moves are largely transmitted to the real short term rate also, due to the stickiness of inflation expectations, at least for short term horizons.

Consequently, substituting the real IRG for the sole real interest rate should help in restoring empirically the missing negative correlation suggested by the theory.

To begin with, I provide here preliminary in-sample evidence of the informational content of the selected interest rate gaps. Table 1 reports the cross correlations of quarterly inflation, the quarterly growth rates of real GDP and real credit and the rate of unemployment with the nominal short term rate of interest, the *ex post* short term real rate, as well as the various IRG estimates obtained. The computations are shown for the period 1986-2004, for which the rate of HICP inflation and the real interest rate in the reconstructed Euro area may be reasonably deemed stationary, but computations over different periods (e.g. from 1979 or 1991 on) lead to qualitatively similar results.

[insert Table 1 about here]

Interestingly enough, the actual real and nominal interest rates appear to be highly *positively* correlated with future inflation at horizons up to two years ahead. In contrast, IRG estimated on the basis of multivariate UC models exhibit zero to slightly negative correlations with future inflation. Nevertheless, the correlation coefficients for the (one-sided) HJ and MR IRG remain contained (with a maximum absolute value of about 0.1) and stand clearly below the levels displayed in other studies relative to the euro area, notably Giammarioli and Valla (2003), and Garnier and Wilhelmsen (2005) and, but to a lesser extent, Crespo-Cuaresma et al. (2004). Three main reasons may account for the higher negative correlations between inflation and IRG estimates found in the first two of these papers. First, the actual real rate of interest is often highly correlated with their estimated IRG because their NRI estimate exhibit very-limited long run fluctuations and only contained short run volatility. Second, the sample used generally includes the high inflation episode of the 1970s and the high nominal rate episode of the early 1980s, which explains most of the strong negative correlation between inflation and the real rate of interest obtained over the last few decades, hence between inflation and the estimated real IRG[12]. As a matter of fact, the correlation coefficients between inflation and the MR one-sided IRG over its whole period of availability (since 1979) are consistently higher in absolute terms and negative (up to -0.23 with a two years lag)[13]. Finally, a possible explanation that has already been put forward by some authors (e.g. Larsen and McKeown, 2004) is that, in the 1990s, the policy maker may have better used *ex ante* the informational content for inflation that is more or less captured in real IRG estimates, which would have reduced *ex post* the cross correlations between the objective variable -inflation- and lags of the real IRG.

Regarding the informational content for real activity and unemployment, univariate IRG estimates exhibit relatively strong negative cross correlations at horizons less than one year with future output growth, while short term nominal and real interest rates appear to be at best uncorrelated with this variable. However, the univariate gaps show also strong negative correlations to future rates of unemployment. The results related to multivariate estimates are however mixed. One-sided HJ and MR IRG estimates are negatively but poorly correlated to future output growth, while the MR gap appears to be strongly positively correlated to future unemployment. Indeed, it appears that the rate of unemployment fluctuates more in synch with the output gap estimated within the MR model (which is directly driven by the IRG) than output growth does, as shown by Figure A.2 in Appendix, as well as the computation of the empirical correlation coefficients (0.64 for the correlation between unemployment and the MR output gap, to be compared with only 0.16 for the correlation between this output gap and quarterly annualized growth). Last but not least, all gaps (excepted the HJ IRG), as well as levels of the interest rates, exhibit strong in-sample correlations with future credit growth, including at somewhat distant horizons.

[12] For instance, the correlation between quarterly inflation and past values of the ex post real interest rate over 1979-2004 is negative for lags superior to two quarters, increases with time lag and reaches -0.34 with a two years lag (instead of +0.52 over 1986-2004).

[13] The results are not reproduced here for brevity. However, the correlations obtained over the 1979-2004 period are likely to be spurious due to the plausible non-stationarity of inflation and interest rates series, so they deserve to be considered with caution.

5. A simulated out-of-sample forecasting experiment

5.1. Methodology of the forecasting simulation

In order to investigate the forecasting power of various measures of the short term real interest gap for macroeconomic variables, I simulated a classical out-of-sample forecasting exercise (see e.g. Stock and Watson, 1999).[14] I thus consider a forecasting equation of the general form:

$$(5.1) \qquad y_{t+h,t} = \alpha + \gamma(L)y_{t-1} + \beta(L)x_{t-1} + u_t$$

where $y_{t+h,t}$ is the annualised h-step forward rate of growth of the variable of interest Y_t, y_t its annualised quarterly rate of growth, X_t is a candidate leading indicator, γ and β are polynoms in the lag operator L and h denotes the horizon of the forecast in quarters. Importantly for the realism of the experiment, it has to be noticed that the usual reporting lags imply that GDP and even price data that are required to compute IRG estimates for quarter t are only known in the curse of quarter t+1. In order to account for this, I forecast $y_{t+h,t}$ with data for quarters *t-1* and earlier.

The precise definition of $y_{t+h,t}$ depends on the degree of integration of the forecast variable. If Y_t stands for a variable (in logs) which is deemed to be integrated of order one, then we have:

$$(5.2) \qquad y_{t+h,h} = \tfrac{400}{h}.\left(Y_{t+h} - Y_t\right)$$

Conversely, if we assume Y_t to be integrated of order two, then y_t in equation (5.1) refers to the first difference of the quarterly rate of growth of Y_t (annualised), and we have, following the approach in Stock and Watson (1999, 2003):

$$(5.3) \qquad y_{t+h,t} = 400\left[\frac{1}{h}(Y_{t+h} - Y_t) - (Y_t - Y_{t-1})\right]$$

[14] Recent applications of this methodology to Euro area data include Nicoletti-Altimari (2001), Le Bihan and Sédillot (2000), and Nobili (2005).

Once this definition adopted, I proceeded in the following way. Equation (5.1) is first estimated for a given regressor X_t and for a given forecast horizon h over the "initial" sample of data (up to period R). The degrees of polynoms γ and β are automatically and jointly selected on the basis of the Akaike information criterion (AIC), with a maximum of four lags allowed for each regressor[15]. A h-step ahead forecast $y_{R+h,R}$ is then computed using the estimated equation and the corresponding h-step forecast error is stored. A new quarter of data is then added to the regression sample (the sample window includes now R+1 observations). Equation (5.1) is re-estimated over that new sample, with the number of lags of the RHS variables again automatically selected and the whole procedure is repeated until the regression sample reaches the end of the available series.

For each model M(Y,X,h), i.e. each candidate leading indicator of the variable to be forecast and each forecast horizon h, this produces a series of out-of-sample forecast errors. If we denote as P the number of out-of-sample observations (P=T-R, where T is the total number of observations), the number of forecast errors obtained is equal to P-h+1. The predictive content of model M(Y,X,h) is then summarised in a standard way in terms of a root mean of squared forecast errors (RMSE).

As is usual for such an exercise, the forecasting accuracy of model M(Y,X,h) is assessed against a benchmark autoregressive model for $y_{t+h,t}$, taking the form :

$$(5.4) \qquad y_{t+h,t} = \alpha + \chi(L)\, y_{t-1} + v_t$$

For a given autoregressive model M'(Y,h) corresponding to equation (5.4), a series of out-of sample forecast errors is produced using the same recursive procedure as above, the lag length of the dependent variables in (5.4) being selected automatically at each step according to the Akaike information criterion (AIC)[16].

[15] These limits are common, see for instance Kamada (2005). Besides it has been observed that allowing a maximum of eight lags does not change the results, the number of required lags remaining generally below four.

[16] It should be noted that for contemporaneous estimations of concurrent models M and M', the lag length p and p' are not required to be identical, which means that the models may be non-nested.

5.2. *Real-time interest rate gaps*

When they try to get an estimate of the neutral level of the real interest rate – as well as of the NAIRU or potential output-, policy-makers face three sources of uncertainty in real time: first, the underlying data (in particular GDP, which is here key for the multivariate unobserved-components models) are usually revised by statisticians; second, the addition of new data may change the assessment, including the reading of past quarters (this is often referred to as the "end-of-sample problem"); third, the information added by new data or revisions may invite to modify the econometric models underlying the assessment or at least to re-estimate their parameters. With this in mind, four stages in the measurement process of real IRG can be defined: real-time, quasi-real time, quasi final and final[17]. The "final" IRG estimate is computed using the latest vintage of underlying data over the whole period under review (here the period spanning from the first quarter of 1979 to the third quarter of 2005, using "final" data releases as of end of May 2006) to eventually fit a model and "detrend" the real interest rate[18]. On the contrary, supposing that vintages of real-time data sets are available for each quarter, each vintage of the real time real interest rate can be "detrended" with one of the chosen techniques to construct a set of real time IRG series. In case of model-based approaches, this in particular implies also that the model parameters have to be re-estimated for each real-time vintage. Quasi-real time and quasi-final estimates are located between these two extremes. The quasi-real time IRG series are simply the rolling IRG series estimates based on the final data set (hence allowing for changes in underlying model parameters with the addition of new data). Lastly, in case of multivariate UC models like the HJ and MR models, I define the quasi-final IRG series as the one-sided (filtered) IRG series estimated both with the final dataset and fixed full-sample estimates of the model parameters[19].

[17] I follow here the typology first proposed by Orphanides and Van Norden (2002).

[18] The term vintage is generally used to describe the values for data series as published at a given point in time.

[19] Note that in case of the HP filtered real interest rate gap, for which no parameter are estimated, the quasi-real time and quasi-final series estimated over a given sample are identical.

Figure 2 shows real time and final IRG estimates from various methods. Interestingly, the quasi-real MR and HJ IRG are close to the corresponding quasi-final estimates of the gap, which highlights the small impact of new data on parameters estimates of these models (hence their prove quite robust to change in sample). However, the true real-time MR gaps depart substantially from the quasi-real-time ones (up to one percentage point in some quarters). This suggests that the impact of GDP revisions on the outcome should not be neglected.

[insert Chart 2 about here]

A distinct ensemble of real time IRG vintages is thus constructed for each estimation technique. For a given technique, the first real-time IRG series is estimated over 1979Q1 to 1998Q4 (for use in forecasts made in 1999Q1), and successive series are estimated for increasing samples up to 2005Q3 (corresponding to the information available in 2005Q4). The data set comprises then 28 quasi-real-time IRG series for each estimation technique.

5.3. Forecast variables

The forecasting simulations have been carried out for four dependant variables of interest, HICP inflation, real GDP growth, the quarterly change in the rate of unemployment and the real rate of growth of credit to the private sector.

Although in the Euro area the mandate of the ECB confers a prominent weight to the objective of price stability, the practice of major central banks converges in acknowledging some weight for a concomitant real stabilization objective, at least in the short run, as advocated for instance by the proponents of flexible inflation targeting schemes (see for instance Faust and Henderson, 2004, and references therein). This (implicit) dual objective being usually conceived in terms of volatility of the output gap, this would invite to consider output gap measures among the projected variables. The emphasis on real GDP growth instead of some measure of the output gap aims at avoiding complex and still inconclusive debates about the best proxy for this unobservable variable, having in mind that the commonly used statistical output gap estimates (HP filters, UC models) as well as those derived from ad hoc production functions do not match theory-based definitions of the gap as the difference between actual output and its flexible prices counterpart[20]. Besides it can be argued that some major central banks in the past may have focused more on the *change* in the output gap (that is output growth less potential output growth) than on the *level* of the output gap itself[21].

Finally, the inclusion of real credit growth among the set of variables to be forecast could be justified both by the emphasis put by the ECB on its monetary pillar, since credit to the private sector makes up the bulk of the broad monetary aggregate counterparts, and by concerns for financial stability[22]. Besides, with a reference to the genuine Wicksellian framework (Wicksell, 1898), the excess demand arising from a negative IRG should materialize through the build-up of an excess demand for credit which the banking system would accommodate, leading to both inflationary pressures and the build-up of financial imbalances. Hence, investigating the effect of a non-negative IRG on credit developments seems to be fully relevant from a Wicksellian perspective.

For each macroeconomic variable of interest and each estimation technique of the real IRG, the forecasting exercises have been conducted with horizons of two, four and six quarters. Beside the already presented IRG, I also test for the predictive power of a simple alternative candidate, the first difference in the short term nominal interest rate (hereafter DSTN model). Under the assumptions of sticky enough yearly inflation and natural rates from one quarter to the next, changes in the nominal interest rate can be viewed as proxy of changes in the real IRG. Furthermore, using changes in the nominal rate in this way is arguably equivalent to

[20] Nevertheless, I also checked the predictive power of competing IRG measures for three alternative simple statistical (final) estimates of the output gap filtered with a smooth HP filter and two standard band-pass filters, namely the Baxter-King and the Christiano-Fitzgerald filters. None of the selected IRG helps to improve forecasts of any of these statistical output gaps. Results are available upon request.

[21] For the Bundesbank, see Gerberding and al. (2005), for the US, see e.g. Walsh (2002).

[22] cf. Borio et al. (2003) for a general statement and Issing (2002) for the view of the ECB.

implicitly defining an estimated IRG as a one-sided filter of interest rate changes with weights based on the estimated coefficients in Equation (5.1)[23].

According to preliminary stationarity tests (see Appendix C), the majority of the differenced series to be forecast (i.e. real growth rates of GDP and credit and the rate of change in the unemployment rate) as well as real IRG may be deemed to be stationary. An important exception is HICP inflation, which appears to be integrated of order one over the observation sample. Depending on the diagnosis about the order of integration of the dependant variable, the choice of the forecasting model was made as explained in section 5.1. Forecasts relate then to the average future rate of GDP, credit and unemployment growth over the forecasting period on the one hand, and to the difference between average future inflation and current inflation on the other hand.

Table 2 presents the results of the baseline forecasting exercises. For each possible dependant variable, the first row of the corresponding sub-Table reports the root mean squared error (RMSE) of the benchmark AR model at each forecasting horizon *h*, while the following rows give the ratios of the RMSE of alternative models to the RMSE of the AR model. A given model is credited with some informational content about future inflation when the corresponding RMSE ratio stands below unity. Note that since AR models of either inflation or GDP growth etc. are probably poor models of these respective variables, this comparison offers only a weak test of the informational content of interest rate gaps estimates for the macroeconomic variables of interest.

[insert Table 2 about here]

5.4. Forecast evaluation

An interesting issue is to determine whether the improvement in forecast accuracy observed at some point is statistically significant. Several tests of forecast accuracy have been

[23] Considering the case of output gap estimation and following St-Amant and van Norden (1998), Orphanides and van Norden (2005) refer to such estimates as TOFU gaps (Trivial Optimal Filter Unrestricted).

proposed in the literature, among which the popular Diebold and Mariano (1995) DM test. However, the use of the DM test in this context is highly debatable[24].

First, the distribution of the test statistic is only asymptotically normal. Hence, with a maximum of 26 out-of-sample forecast errors, the true distribution of the test statistic may differ significantly from the asymptotical one (small sample bias)[25]. Second, the use of DM test is justified in the case of non-nested models only, which may not be the case when the augmented regressions as in Equation (5.1) are run against the benchmark AR model[26]. In a recent paper, Clark and McCracken (2005) showed indeed that, for multi-step forecasts and nested models, the asymptotic distributions of the DM test is non-standard and affected by unknown nuisance parameters[27]. Consequently, they suggest alternative tests for nested models, the MSE-F and ENC-F tests. I thus implement the MSE-F test to evaluate the gain in forecast accuracy against the AR benchmark. Since the conditions of application of the asymptotic critical values are clearly rejected due to the small size of the forecast sample, I resort to a bootstrap strategy of the kind proposed by Orphanides and van Norden (2005). The MSE-F test takes the form :

$$MSE - F = P\frac{(MSE_1 - MSE_2)}{MSE_2}$$

Where P is the number of forecasts (decreasing with the forecast horizon h), $MSE1$ is the mean squared forecast error of the benchmark (AR) model and $MSE2$ the mean squared forecast error of the competing IRG augmented model. The distribution of the statistic under the null assumption of no gain in forecast accuracy (i.e. of equal MSE) is obtained via a bootstrap experiment with 200 replications, as detailed in Appendix D. Since theses

[24] See for instance Kunst (2003) for a recent critical assessment of the DM test.

[25] Le Bihan and Sedillot (2000) consider that with 72 observations, the use of asymptotic results is relevant. Orphanides and van Norden (2005) also provide with DM statistics for samples of about 50 observations. However, while focusing on the (simpler) case of one-step ahead forecasts, Clark and McCracken (2005) warn against the use of asymptotical critical values when the ratio of the number of forecasts to the number of in-sample observations is superior to 10% (which would imply in our case IRG and inflation series for the "euro area" beginning in… the mid-1930s).

[26] Even if I allow the lags of the dependant variable and the candidate IRG to differ, they can both be capped at four.

[27] The same holds for the test of forecast encompassing proposed by Harvey, Leybourne and Newbold (1998).

distributions are non pivotal, the test statistics are estimated anew for each model M(Y,X,h), that is for each dependant variable/IRG combination and each forecasting horizon[28].

When the competing IRG augmented models are assessed against the DSTN benchmark, the forecasting models to be compared are no longer nested, so one can use the DM test. The test statistic is computed as follows:

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi\hat{f}(0)}{P}}}$$

where $\bar{d}$ is the mean of the difference in squared forecast errors between the DSTN and the IRG-augmented models and $\hat{f}(0)$ is an estimator of its spectral density at frequency zero. I use:

$$2\pi\hat{f}(0) = \hat{\Gamma}_{0,P} + \sum_{j=1}^{m}\left\{1-\left(\frac{j}{m+1}\right)\right\}\left(\hat{\Gamma}_{j,P} + \hat{\Gamma}'_{j,P}\right)$$

where $\hat{\Gamma}_{j,P} = (1/P)\sum_{t=j+1}^{P}(d_t - \bar{d})(d_{t-j} - \bar{d})$ is the estimated auto-covariance of d_t at lag j. I choose $m = 4(P/100)^{(2/9)}$, so that $2\pi\hat{f}(0)$ is the standard Newey-West (1987) HAC robust estimator of the long run variance of d_t.

Nevertheless, as pointed by Orphanides and van Norden (2005), the underlying asymptotic theory of these tests do not allow for changing lags in the forecasting equation during the recursive estimation procedure, nor for changing data sets. Besides, the variables used in the regressions should not be themselves estimated. All these conditions are clearly violated here, so the tests' diagnostics as reported in Tables 2 and 3 should be considered as indicative only.

[28] This bootstrap procedure is computationally very intensive: the estimation of the simulated p-values of one panel of Table 2 or 3 requires for instance 200*3*8*24*16=1,843,200 regressions.

6. Results of the out-of-sample simulations

None of the estimated IRG displays significant leading indicator properties for future inflation (see Tables 2 and 3). However, this negative result of the out-of-sample experiment could have been largely anticipated, considering both the sign of in-sample correlations and the theoretically only indirect impact of a non-zero IRG on inflation.

Turning to forecast of fluctuations in measures of real activity, the results are more promising. Indeed, the MR gap, along with the simple QT gap, help to significantly improve forecasts of output growth at horizons longer than one year. Remarkably, the performance of the MR gap in quasi real time is confirmed with real time estimates, although it deteriorates slightly, thus accounting for the impact of GDP revisions on forecast accuracy. However, a closer look at Tables 2 and 3 together suggest that none of these two gaps significantly improves the forecasting performance of a simple AR model augmented with lagged interest rate changes (the DSTN model).

Similarly, according to the results in Table 2, the MR and DSTN indicators prove to have a significant predictive content for changes in the rate of unemployment, along with the smoothest HP gap (HP2). As for forecasts of output growth, the reduction in RMSE also increases with the forecasting horizon (up to 30% for the MR IRG at six quarters). In contrast however, the comparison with Table 3 indicates an informational advantage of the MR gap over the simple change in the nominal interest rate (with cuts RMSE of around 15%, even if the associated simulated p-values of the DM test are greater than 10%).

Finally, the MR gap stands out as a promising leading indicator of credit developments, at forecasting horizons up to one year ahead. As a matter of fact, it seems to add information both to the simple AR and the DSTN models of real credit growth, even when real time data are used.

[insert Table 3 about here]

A few robustness checks have been performed that confirm qualitatively these results. Table 4 first presents the outcome of the same out-of-sample exercise over a longer period beginning at the end of 1994 (i.e. the first one-quarter ahead forecast are computed as in 1995Q1), a year that marks the start of Stage II of European and Monetary Union (EMU) with the creation of the former European Monetary Institute (which became the ECB in 1998)[29]. Some of the previous conclusions remain valid. Introducing lags of the MR IRG into an AR model of unemployment and credit growth still leads to a substantial reduction of the forecast RMSE at projection horizons from 2 to 6 quarters. However, simpler models, the HP2 and DSTN models, perform also relatively well. Besides, the latter and the QT models are associated with an improved forecast accuracy for GDP growth. In contrast, the gain in forecast accuracy associated with the MR model for GDP growth vanishes while one extends the out-of-sample period.

Another possible source of sensitivity of the results to the forecasting experimental design is the criterion chosen to select the lag structure used in the forecasting equations (5.1) and (5.4). Therefore, to check the robustness of our results to the consequences of this choice, I repeated the whole experiment using the Schwarz information criterion (SIC) instead of the Akaike criterion (AIC). Table 5 displays the results, for simulations beginning in 1999Q1. The results are qualitatively unchanged, whatever the chosen criterion for lag selection, with a few exceptions. Simple univariate IRG (HP and CF) perform now quite well in inflation models, especially at longer horizons. Conversely, the predictive content of the MR gap for future output growth is not confirmed.

[insert Tables 4 and 5 about here]

[29] The creation of the EMI makes more plausible, for the purpose of this experiment, the assumption of a policy maker who would be interested in forecasting euro area inflation and growth. Such a choice is not uncommon for studies of the forecasting power of various indicators for key policy variables in the euro area. Another recent example is provided by Nobili (2006).

7. Conclusion

I aim in this paper at assessing the empirical usefulness for the ECB of a real interest rate gap (IRG) estimate for the Euro area that is derived from a semi-structural approach, as compared to purely statistical detrending techniques. The techniques used are standard, but their application to real IRG estimates is novel, in spite of a growing empirical literature on the "natural" rate of interest, in the Euro area as well as in the US and other industrialised countries. The assessment is based on simulations of out-of-sample forecasting experiments, as in e.g. Stock and Watson (1999). In a standard way, the forecasting performance of simple autoregressive models of inflation, GDP growth and other macro variables that are augmented with IRG estimates is compared with the forecasting accuracy of benchmark AR models. It is well-known that such simulated experiments should be conducted using real-time data, in order to replicate in a credible way the true situation facing policy makers when they have to meet decisions. I therefore construct such a real time dataset for Euro area GDP since the inception of the euro and compute real-time as well as quasi-real-time estimates of the candidate IRG measures.

A robust finding is that the semi-structural IRG measure employed in Mésonnier and Renne (2006) has a significant predictive power in real time for unemployment and for credit growth four to six quarters ahead. Noticeably also, a simple detrended real interest rate series -that is corrected either by a quadratic trend or a smooth HP trend- tends to exhibit noticeable forecasting performance for either real GDP growth or unemployment. These results are robust to both changes in the period where the experiment is conducted and the choice of the lag selection technique in the forecasting regressions. Nevertheless, in most cases, the gain in forecasting power over a simple AR model augmented with the variations of the nominal interest rate (the DSTN model) is not clear-cut. One exception remains however the good predictive power of the Mésonnier-Renne IRG for future credit growth. In contrast, the simulations suggest that computed IRG estimates are globally of little help to improve Euro area inflation forecasts in real time.

The conclusion of this exercise is then mixed, as could have been reasonably expected considering previous results concerning the limited real-time policy relevance of output gap estimates (Orphanides and van Norden, 2005). However, nobody should reasonably expect a single indicator to subsume all the relevant information required by the monetary policy-maker in real time. Mixed as they are, the results of this study nevertheless do not invalidate the view that semi-structural estimates of the natural rate of interest deserve being included into the broad-based informational set usually considered by modern central banks in practice.

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Appendix A. Data issues

Table A.1: description of the real-time database for euro area GDP

Cut-off date	Observation quarter	Last available quarter
04/03/1999	1999Q1	1998Q4
02/07/1999	1999Q2	1999Q1
06/10/1999	1999Q3	1999Q2
10/12/1999	1999Q4	1999Q3
16/03/2000	2000Q1	1999Q4
09/06/2000	2000Q2	2000Q1
14/09/2000	2000Q3	2000Q2
12/12/2000	2000Q4	2000Q3
10/04/2001	2001Q1	2000Q4
04/07/2001	2001Q2	2001Q1
13/09/2001	2001Q3	2001Q2
05/12/2001	2001Q4	2001Q3
03/04/2002	2002Q1	2001Q4
05/06/2002	2002Q2	2002Q1
11/09/2002	2002Q3	2002Q2
04/12/2002	2002Q4	2002Q3
05/03/2003	2003Q1	2002Q4
04/06/2003	2003Q2	2003Q1
03/09/2003	2003Q3	2003Q2
03/12/2003	2003Q4	2003Q3
31/03/2004	2004Q1	2003Q4
30/06/2004	2004Q2	2004Q1
01/09/2004	2004Q3	2004Q2
01/12/2004	2004Q4	2004Q3
02/03/2005	2005Q1	2004Q4
01/06/2005	2005Q2	2005Q1
05/10/2005	2005Q3	2005Q2
01/12/2005	2005Q4	2005Q3

Chart A.1: initial data set

Annual rates of growth in logs, excepted short term interest rate in %.

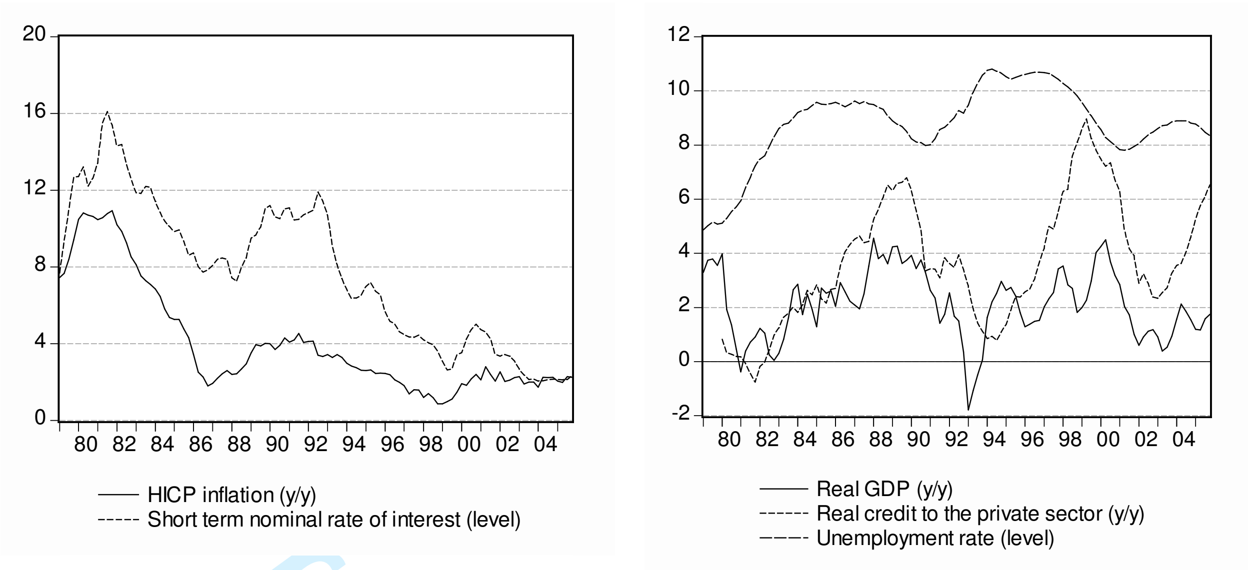
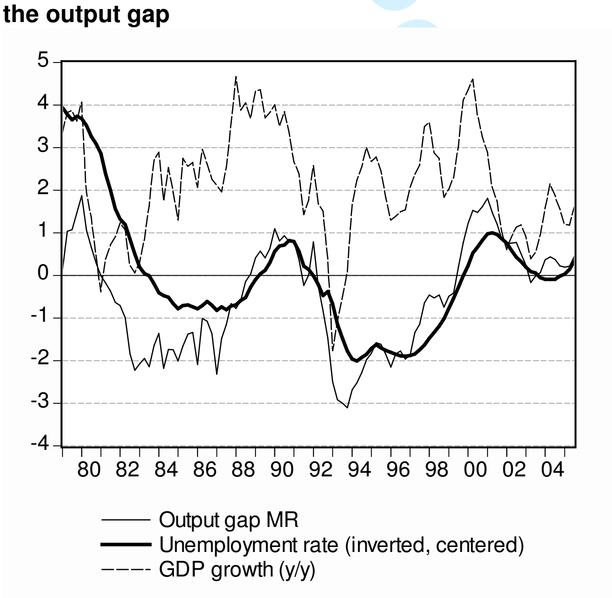


Chart A.2: rate of unemployment and MR estimate of the output gap



Appendix B. Multivariate Unobserved components models

B.1. A multivariate unobserved-components (UC) model: the Harvey-Jaeger model

Multivariate unobserved component (UC) models estimated with the Kalman filter offer a general framework for decomposing macroeconomic time series into unobserved trend and cycle, allowing for explicit dynamic structure for these components and accounting for interactions between theoretically related variables. I consider here a multivariate version of the Harvey and Jaeger (1993) model, which has been applied recently to the issue of NRI estimation in the euro area (see Crespo-Cuaresma et al., 2004). Let us suppose that the observed vector of time series $z_t = (r_t, y_t, \pi_t)'$, whose components are the ex post real interest rate, (log of) real GDP and the rate of quarterly inflation respectively, can be decomposed into the sum of a trend, a cycle and an irregular component:

$$(2.2.1)\quad z_t = \mu_t + \varphi_t + \varepsilon_t$$

By assumption, the multivariate trend component μ_t is defined as a local linear trend, that is to say a random walk with drift where the drift itself follows a random walk:

$$(2.2.2)\qquad \mu_t = \mu_{t-1} + g_t + \tau_t$$
$$(2.2.3)\qquad g_t = g_{t-1} + \varsigma_t$$

The stochastic cyclical component is then specified as a sine-cosine wave with a dampening factor:

$$(2.2.4)\quad \begin{pmatrix} \varphi_t \\ \varphi_t^* \end{pmatrix} = \rho \left[\begin{pmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{pmatrix} \otimes I \right] \begin{pmatrix} \varphi_{t-1} \\ \varphi_{t-1}^* \end{pmatrix} + \begin{pmatrix} \kappa_t \\ \kappa_t^* \end{pmatrix}$$

The errors in equations (2.2.1) to (2.2.4) are assumed to be i.i.d mean-zero, Gaussian, mutually uncorrelated processes. Nevertheless, the two disturbance terms in (2.2.4) are constrained to have the same variance. Following Crespo-Cuaresma et al. (2004), I limit to the case where the variance of τ_t in equation (2.2.2) is assumed to be null, which implies a smoother trend component and empirically tends to improve the fit of the model[30].

B.2. A semi-structural UC model: the Mésonnier-Renne model

The MR approach of the NRI for the euro area consists in estimating a simple restricted VAR model of the euro area economy with the Kalman filter. The focus is on a medium-

[30] The Kalman filtering procedure requires to set some initial conditions regarding the mean and covariance matrix of the unobserved variables. As commonly done, simple diffuse priors (HP filtered trends) are used to guess plausible initial conditions. Besides, I initialize the procedure of likelihood maximization over the vector of parameters using values close to the results of the baseline model in Crespo-cuaresma et al. (2004) –correcting for the different frequency of the data sets-. In particular, the initial value for λ is set to 0.52, which corresponds to short business cycles of three years (possibly related to

term notion of the real natural interest rate, which can be described as a "non accelerating-inflation rate of interest" (NAIRI). The NRI is assumed to be correlated with the low frequency fluctuations of potential output growth, both following a stationary process. Inflation expectations one-quarter ahead, which are required to deflate the short term nominal rate of interest and compute an *ex ante* real rate of interest, are supposed to be rational and are inferred from the model. The model consists then in the following six equations:

$$\begin{cases} (2.3.1) \quad \pi_t = \alpha_1 \pi_{t-1} + \alpha_2 \pi_{t-2} + \alpha_3 \pi_{t-3} + \beta z_{t-1} + \varepsilon_t^{\pi} \\ (2.3.2) \quad z_t = \Phi z_{t-1} + \lambda (i_{t-2} - E_{t-2}(\pi_{t-1}) - r_{t-2}^*) + \varepsilon_t^z \\ (2.3.3) \quad r_t^* = \mu_r + \theta a_t \\ (2.3.4) \quad \Delta y_t^* = \mu_y + a_t + \varepsilon_t^y \\ (2.3.5) \quad a_t = \psi a_{t-1} + \varepsilon_t^a \\ (2.3.6) \quad y_t = y_t^* + z_t \end{cases}$$

where π, i, y, z, r^* and Δy^* stand for quarterly inflation (annualized), the nominal short term rate of interest, real GDP, the output gap, the natural real interest rate and potential output growth respectively. Lags of the dependant variables in the first two equations are selected by the data and the hypothesis of an accelerationist form of inflation (i.e. that the coefficients of lagged inflation sum to unity) is not rejected empirically. The ψ parameter is estimated to be close to but less than unity.

The first equation can be interpreted as a backward-looking Philips-curve, the second as an IS-curve. The remaining equations state the dynamics of the natural rate and of potential output growth and define the output gap. According to this model, stable inflation is thus consistent with both null output and interest rate gaps and a departure of the real interest rate from its neutral level affects quarterly inflation with a lag of three quarters. Interestingly, no equation for the nominal rate of interest is stated, which means that the monetary policy reaction function remains implicit. Complete model estimation by maximization of the

the cycle of inventories, as argued by Bentoglio et al., 2002) and the initial attenuation factor ρ is postulated to be 0.85 (which corresponds to a half-life of cyclical shocks of 5 quarters).

likelihood requires the calibration of the ratio of the variances of innovations to potential output growth and the output gap on the one hand, and of the θ parameter analogous to a constant relative risk aversion of consumers (see Mésonnier and Renne, 2006, for details).

Appendix C. Preliminary unit root tests

Table C

Sample 1979-2005		ADF		PP		KPSS
		test	pvalue	test	pvalue	test
PI	+C	-1.12	0.70	-1.43	0.57	0.80
D(PI)	+C	-11.56	0.00	-16.20	0.00	0.07
RR	+C	-0.97	0.76	-0.83	0.81	0.64
D(RR)	+C	-8.93	0.00	-8.94	0.00	0.42
Y	+C	-8.11	0.00	-8.40	0.00	0.09
U	+C	-2.81	0.06	-2.68	0.08	0.39
D(U)	+C	-3.46	0.01	-3.51	0.01	0.43
L	+C	-1.68	0.44	-2.12	0.24	0.43
PI	+C+T	-1.35	0.87	-2.88	0.17	0.21
D(PI)	+C+T	-11.52	0.00	-16.12	0.00	0.07
RR	+C+T	-2.01	0.59	-1.77	0.71	0.30
D(RR)	+C+T	-9.05	0.00	-9.50	0.00	0.08
Y	+C+T	-8.08	0.00	-8.38	0.00	0.08
U	+C+T	-2.31	0.43	-1.99	0.60	0.21
D(U)	+C+T	-4.09	0.01	-4.25	0.01	0.08
L	+C+T	-2.12	0.53	-3.11	0.11	0.08

Legend : PI = quarterly rate of inflation (annualised, in logs), D(PI) = first difference of inflation, RR = real interest rate (ex post, deflated using annual inflation), D(RR) = first difference in RR, Y = quarterly rate of growth of real output (annualised, in logs), U = rate of unemployment (in levels), D(U) = quarterly rate of growth of the rate of unemployment (annualised, in logs), L = quarterly rate of growth of real credit to the private sector (annualised, in logs). Number of lags in ADF and PP automatically adjusted using the AIC.

Appendix D. Bootstrap methodology for estimation of the probabilities associated with the DM and MSE-F tests statistics

The distributions of the MSE-F and MSE-T (or DM) statistics presented in Section 5.4 are estimated for each forecast variable/forecasting model combination via a bootstrap experiment (see Clark and McCracken, 2005 and Orphanides and van Norden, 2005, for similar approaches).

In a first step, I estimate a constrained VAR in the forecast variable (e.g. the first difference of HICP inflation) and a candidate IRG estimate (e.g. the final HP1 IRG), under the null assumption that the IRG does not Granger cause the forecast variable. The number of lags in the VAR is selected on an equation-by-equation basis using the AIC, with an allowed maximum of 8. Residuals of the VAR are drawn with replacements and plugged into the estimated VAR, so as to reconstruct 200 simulated datasets of 108 observations each (equivalent to series spanning the period from 1979Q1 to 2005Q4). For each dataset, the first values (up to the required number of lags in the estimated VAR) are taken from historical data, from a randomly chosen date onward.

In a second step, using each simulated pair of series, I perform an out-of-sample forecasting experiment equivalent to the one presented in section 4.1 and store the corresponding test statistics computed for each forecasting horizon.

In the case of the UC models, whose outcome is normally affected by revisions of GDP data, I nevertheless considered the quasi-final version of the IRG as a proxy for the real-time version of the gap because of the difficulty inherent in defining how to bootstrap revisions of the estimated IRG over time.

Table 1: Cross correlations over 1986-2005, quarterly rates of growth (annualised)

Period : 1986Q1-2004Q4	k=1	k=2	K=3	k=4	k=5	k=6	k=7	k=8
HICP Inflation (t+k)								
NR	0.63	0.61	0.58	0.54	0.50	0.49	0.45	0.40
RR	0.56	0.56	0.53	0.52	0.50	0.50	0.50	0.49
DSTN	0.14	0.20	0.27	0.26	0.12	0.26	0.31	0.23
IRG QT	0.49	0.50	0.46	0.46	0.43	0.44	0.44	0.43
IRG HP1	0.16	0.16	0.09	0.08	0.04	0.07	0.08	0.09
IRG HP2	0.43	0.43	0.36	0.35	0.31	0.31	0.31	0.30
IRG CF	0.14	0.14	0.07	0.06	0.03	0.05	0.06	0.06
IRG HJ one-sided	-0.05	-0.02	-0.08	-0.07	-0.11	-0.08	-0.06	-0.03
IRG MR one-sided	0.14	0.11	0.02	0.00	-0.03	-0.03	-0.03	-0.02
Real GDP growth (t+k)								
NR	-0.01	-0.05	-0.05	-0.02	-0.01	-0.02	-0.00	0.02
RR	0.03	0.00	0.03	0.07	0.09	0.09	0.09	0.09
DSTN	0.24	-0.04	-0.15	-0.06	0.02	-0.07	-0.16	-0.00
IRG QT	-0.30	-0.36	-0.28	-0.18	-0.13	-0.10	-0.09	-0.08
IRG HP1	-0.35	-0.42	-0.27	-0.11	-0.04	0.01	0.02	0.03
IRG HP2	-0.33	-0.40	-0.30	-0.17	-0.12	-0.09	-0.08	-0.08
IRG CF	-0.31	-0.39	-0.26	-0.12	-0.06	-0.02	-0.01	-0.01
IRG HJ one-sided	-0.07	-0.23	-0.16	-0.03	0.05	0.11	0.15	0.18
IRG MR one-sided	-0.11	-0.08	0.02	0.07	0.18	0.21	0.28	0.30
Rate of unemployment (t+k)								
NR	0.04	0.09	0.15	0.21	0.27	0.34	0.39	0.44
RR	0.12	0.15	0.20	0.24	0.29	0.33	0.36	0.38
DSTN	-0.34	-0.39	-0.39	-0.39	-0.39	-0.34	-0.30	-0.27
IRG QT	-0.54	-0.45	-0.33	-0.22	-0.12	-0.02	0.05	0.11
IRG HP1	-0.31	-0.23	-0.14	-0.06	0.01	0.07	0.08	0.09
IRG HP2	-0.44	-0.35	-0.24	-0.14	-0.04	0.04	0.10	0.14
IRG CF	-0.33	-0.27	-0.19	-0.12	-0.05	-0.01	0.01	0.02
IRG HJ one-sided	-0.12	-0.13	-0.11	-0.09	-0.05	-0.02	-0.03	-0.04
IRG MR one-sided	0.64	0.70	0.76	0.80	0.81	0.81	0.77	0.72
Real credit growth (t+k)								
NR	-0.31	-0.36	-0.40	-0.43	-0.44	-0.46	-0.45	-0.43
RR	-0.23	-0.27	-0.30	-0.33	-0.34	-0.36	-0.37	-0.36
DSTN	0.35	0.26	0.16	0.06	0.07	-0.05	-0.17	-0.09
IRG QT	-0.18	-0.28	-0.36	-0.42	-0.44	-0.48	-0.48	-0.46
IRG HP1	-0.09	-0.19	-0.24	-0.28	-0.26	-0.28	-0.25	-0.20
IRG HP2	-0.19	-0.31	-0.38	-0.44	-0.44	-0.48	-0.47	-0.44
IRG CF	-0.04	-0.15	-0.21	-0.27	-0.26	-0.29	-0.28	-0.25
IRG HJ one-sided	0.20	0.14	0.12	0.08	0.12	0.11	0.14	0.22
IRG MR one-sided	-0.45	-0.43	-0.36	-0.30	-0.21	-0.13	-0.04	0.07

Legend : NR = nominal rate (short), RR = ex post real rate (short, deflated by current annual HICP inflation), IRG QT = real rate corrected with quadratic trend, IRG HP1 = HP (1,600) filtered IRG, IRG HP2 = HP (26,500) filtered IRG, IRG CF = Christiano-Fitzgerald (2003) filtered IRG, IRG HJ = Harvey-Jaeger UC model, IRG MR = baseline IRG using the UC model as in Mésonnier and Renne (2006).

Table 2: predictive power of different measures of the real IRG for inflation, real activity and credit growth in real time – Forecast sample: 1999Q1-2005Q4 – Lag selection using the Akaike information criterion

Ratios of RMSE of competing bivariate models to RMSE of the benchmark AR model

Model	H=2	*pvalue*	H=4	*pvalue*	H=6	*pvalue*
			Inflation			
AR	*1.049*		*0.910*		*0.930*	
HJ quasi real time	1.012	*0.560*	0.992	*0.225*	1.000	*0.350*
MR quasi real time	1.023	*0.680*	1.008	*0.405*	0.965	*0.140*
QT	1.040	*0.830*	1.057	*0.765*	1.097	*0.835*
HP1	1.011	*0.550*	0.999	*0.290*	1.014	*0.545*
HP2	1.006	*0.405*	0.985	*0.155*	0.997	*0.280*
CF	1.001	*0.320*	0.988	*0.235*	0.994	*0.300*
HJ	1.008	*0.490*	0.991	*0.225*	1.002	*0.365*
MR	1.021	*0.650*	1.007	*0.405*	0.961	*0.125*
DSTN	0.990	*0.080*	0.961	*0.090*	0.969	*0.165*
			Real GDP growth			
AR	*1.294*		*1.146*		*1.012*	
HJ quasi real time	0.978	*0.145*	0.965	*0.130*	1.022	*0.655*
MR quasi real time	1.179	*0.960*	0.977	*0.190*	0.811	***0.030***
QT	0.983	*0.220*	0.897	***0.030***	0.840	***0.030***
HP1	1.036	*0.695*	1.030	*0.640*	1.017	*0.580*
HP2	0.928	*0.060*	0.937	*0.095*	0.961	*0.180*
CF	1.086	*0.855*	1.094	*0.840*	1.071	*0.780*
HJ	0.973	*0.125*	0.952	*0.115*	1.019	*0.630*
MR	1.218	*0.970*	1.056	*0.645*	0.907	*0.085*
DSTN	0.909	***0.010***	0.906	***0.000***	0.926	***0.035***
			Unemployment rate			
AR	*4.672*		*5.015*		*5.643*	
HJ quasi real time	0.978	*0.160*	1.012	*0.485*	0.942	*0.085*
MR quasi real time	0.858	***0.005***	0.769	***0.005***	0.696	***0.005***
QT	1.146	*0.950*	1.128	*0.825*	1.016	*0.440*
HP1	0.983	*0.190*	0.972	*0.150*	0.915	***0.040***
HP2	0.884	***0.030***	0.890	***0.050***	0.865	***0.035***
CF	0.954	*0.100*	0.955	*0.150*	0.916	*0.065*
HJ	0.981	*0.175*	1.005	*0.375*	0.941	*0.085*
MR	0.860	***0.005***	0.778	***0.005***	0.705	***0.005***
DSTN	0.964	*0.110*	0.895	***0.020***	0.815	***0.000***
Nb of forecasts	26		24		22	

Notes : the entries in italics show the RMSE of the AR forecast, other entries show the ratio of the RMSE of forecasts based on the method specified to the RMSE of the AR forecast. Hence, a ratio below unity denotes an improvement in forecast accuracy. The p-values correspond to the empirical distributions of the two-sided MSE-F test of Clark and McCracken (2005), as obtained by bootstrap. A probability close to zero is indicative of a significant difference in the RMSE. QT = real rate corrected with quadratic trend, HP1 = HP (1,600) filtered IRG, HP2 = HP (26,500) filtered IRG, CF = Christiano-Fitzgerald (2003) filtered IRG, HJ = Harvey-Jaeger UC model, MR = baseline IRG using the UC model as in Mésonnier and Renne (2006), DSTN = first difference in the short term nominal rate of interest.

Table 2 (continued)

Ratios of RMSE of competing bivariate models to RMSE of the benchmark AR model

Model	H=2	*pvalue*	H=4	pvalue	H=6	Pvalue
			Real credit growth			
AR	*1.405*		*1.501*		*1.481*	
HJ quasi real time	1.000	*0.365*	1.019	*0.500*	0.998	*0.355*
MR quasi real time	0.933	*0.120*	0.897	*0.095*	0.976	*0.270*
QT	0.977	*0.235*	0.993	*0.295*	0.986	*0.280*
HP1	0.946	*0.105*	0.973	*0.185*	1.008	*0.510*
HP2	0.969	*0.215*	0.995	*0.355*	1.095	*0.800*
CF	0.933	*0.080*	0.971	*0.210*	1.006	*0.495*
HJ	1.002	*0.385*	1.035	*0.605*	0.999	*0.370*
MR	0.913	*0.090*	0.876	*0.070*	0.942	*0.185*
DSTN	1.018	*0.605*	0.990	*0.230*	1.038	*0.765*
Nb of forecasts	26		24		22	

Notes : the entries in italics show the RMSE of the AR forecast, other entries show the ratio of the RMSE of forecasts based on the method specified to the RMSE of the AR forecast. Hence, a ratio below unity denotes an improvement in forecast accuracy. The p-values correspond to the empirical distributions of the two-sided MSE-F test of Clark and McCracken (2005), as obtained by bootstrap. A probability close to zero is indicative of a significant difference in the RMSE. QT = real rate corrected with quadratic trend, HP1 = HP (1600) filtered IRG, HP2 = HP (7000) filtered IRG, CF = Christiano-Fitzgerald (2003) filtered IRG, HJ = Harvey-Jaeger UC model, MR = baseline IRG using the UC model as in Mésonnier and Renne (2006), DSTN = first difference in the short term nominal rate of interest.

Table 3: predictive power of different measures of the real IRG for inflation, real activity and credit growth in real time – Forecast sample: 1999Q1-2005Q4 – Lag selection using the Akaike information criterion

Ratios of RMSE of competing bivariate models to RMSE of the DSTN model

Model	H=2	*pvalue*	H=4	*pvalue*	H=6	*pvalue*
			Inflation			
DSTN	*1.039*		*0.875*		*0.901*	
HJ quasi real time	1.022	*0.960*	1.032	*0.900*	1.032	*0.870*
MR quasi real time	1.033	*0.835*	1.049	*0.610*	0.996	*0.440*
QT	1.050	*0.980*	1.100	*0.980*	1.132	*0.980*
HP1	1.021	*0.865*	1.040	*0.880*	1.047	*0.850*
HP2	1.015	*0.825*	1.026	*0.780*	1.029	*0.845*
CF	1.010	*0.645*	1.028	*0.850*	1.026	*0.755*
HJRT	1.017	*0.900*	1.032	*0.890*	1.034	*0.850*
MRRT	1.031	*0.845*	1.048	*0.630*	0.992	*0.415*
			Real GDP growth			
DSTN	*1.177*		*1.039*		*0.937*	
HJ quasi real time	1.075	*0.895*	1.064	*0.815*	1.104	*0.840*
MR quasi real time	1.296	*0.955*	1.078	*0.750*	0.876	*0.085*
QT	1.081	*0.655*	0.989	*0.420*	0.908	*0.305*
HP1	1.139	*0.955*	1.137	*0.935*	1.099	*0.990*
HP2	1.020	*0.720*	1.034	*0.840*	1.038	*0.805*
CF	1.194	*0.995*	1.207	*1.000*	1.157	*1.000*
HJRT	1.070	*0.895*	1.051	*0.735*	1.100	*0.850*
MRRT	1.339	*0.975*	1.165	*0.975*	0.980	*0.385*
			Unemployment rate			
DSTN	*4.505*		*4.490*		*4.597*	
HJ quasi real time	1.014	*0.590*	1.130	*0.835*	1.156	*0.855*
MR quasi real time	0.890	*0.105*	0.859	*0.145*	0.854	*0.195*
QT	1.189	*0.740*	1.260	*0.705*	1.247	*0.655*
HP1	1.019	*0.530*	1.085	*0.690*	1.124	*0.755*
HP2	0.916	*0.215*	0.995	*0.375*	1.062	*0.520*
CF	0.989	*0.485*	1.067	*0.625*	1.125	*0.755*
HJRT	1.018	*0.595*	1.123	*0.815*	1.155	*0.855*
MRRT	0.892	*0.105*	0.869	*0.155*	0.866	*0.180*
			Real credit growth			
DSTN	*1.431*		*1.486*		*1.538*	
HJ quasi real time	0.982	*0.180*	1.029	*0.610*	0.961	*0.305*
MR quasi real time	0.916	*0.090*	0.907	*0.085*	0.940	*.145*
QT	0.959	*0.325*	1.004	*0.415*	0.950	*0.365*
HP1	0.929	***0.025***	0.983	*0.335*	0.971	*0.350*
HP2	0.952	*0.095*	1.006	*0.540*	1.054	*0.740*
CF	0.916	***0.005***	0.981	*0.395*	0.969	*0.400*
HJRT	0.984	*0.200*	1.046	*0.675*	0.963	*0.320*
MRRT	0.896	*0.070*	0.885	*0.060*	0.908	*0.080*
Nb of forecasts	26		24		22	

Notes : the entries in italics show the RMSE of the DSTN forecast, other entries show the ratio of the RMSE of forecasts based on the method specified to the RMSE of the AR forecast. Hence, a ratio below unity denotes an improvement in forecast accuracy. The p-values correspond to the empirical distributions of the DM test of Diebold and Mariano (1995), as obtained by bootstrap. A probability close to zero is indicative of a significant difference in the RMSE. QT = real rate corrected with quadratic trend, HP1 = HP (1,600) filtered IRG, HP2 = HP (26,500) filtered IRG, CF = Christiano-Fitzgerald (2003) filtered IRG, HJ = Harvey-Jaeger UC model, MR = baseline IRG using the UC model as in Mésonnier and Renne (2006), DSTN = first difference in the short term nominal rate of interest.

Table 4: predictive power of different measures of the real IRG for inflation, real activity and credit growth - Forecast sample: 1995Q1-2005Q4 – Lag selection using the Akaike information criterion

Ratios of RMSE of competing bivariate models to RMSE of the benchmark AR model

Model	H=2	H=4	H=6	H=2	H=4	H=6	H=2	H=4	H=6	H=2	H=4	H=6
	Inflation			GDP growth			Unemployment			Credit growth		
AR	*0.917*	*0.803*	*0.832*	*1.207*	*1.061*	*0.967*	*4.485*	*5.219*	*6.131*	*1.470*	*1.705*	*1.847*
QT	1.022	1.029	1.061	0.986	0.955	0.913	1.157	1.125	1.034	1.007	1.004	0.996
HP1	0.998	0.985	1.002	1.006	1.022	0.997	1.050	1.048	0.989	0.995	1.011	1.041
HP2	1.007	0.969	0.972	0.957	0.942	0.939	0.902	0.868	0.863	0.897	0.891	0.927
CF	0.990	0.969	0.976	1.061	1.069	1.025	0.988	0.977	0.928	0.951	0.964	0.987
HJ quasi real time	0.997	0.972	0.977	0.987	0.974	0.957	0.993	1.025	0.974	1.011	1.018	1.019
MR quasi real time	1.013	0.990	0.936	1.121	1.205	1.042	0.855	0.789	0.747	0.932	0.899	0.931
DSTN	0.979	0.946	0.942	0.964	0.938	0.928	0.920	0.856	0.800	1.004	0.969	0.986

Notes : the entries in italics show the RMSE of the AR forecast, other entries show the ratio of the RMSE of forecasts based on the method specified to the RMSE of the AR forecast. Hence, a ratio below unity denotes an improvement in forecast accuracy. QT = real rate corrected with quadratic trend, HP1 = HP (1,600) filtered IRG, HP2 = HP (26,500) filtered IRG, CF = Christiano-Fitzgerald (2003) filtered IRG, HJ = Harvey-Jaeger UC model, MR = baseline IRG using the UC model as in Mésonnier and Renne (2006), DSTN = first difference in the short term nominal rate of interest.

Table 5: predictive power of different measures of the real IRG for inflation, real activity and credit growth - Forecast sample: 1999Q1-2005Q4 – Lag selection using the Schwarz information criterion

Ratios of RMSE of competing bivariate models to RMSE of the benchmark AR model

Model	H=2	H=4	H=6	H=2	H=4	H=6	H=2	H=4	H=6	H=2	H=4	H=6
	Inflation			GDP growth			Unemployment			Credit growth		
AR	*1.098*	*0.975*	*1.014*	*1.285*	*1.146*	*1.012*	*4.507*	*5.015*	*5.303*	*1.389*	*1.543*	*1.645*
HJ quasi real time	0.952	0.926	0.906	0.991	0.994	1.046	0.998	0.965	0.967	1.012	1.023	1.023
MR quasi real time	1.005	0.987	0.987	1.293	1.169	1.024	0.908	0.769	0.740	0.927	0.877	0.910
QT	0.990	0.987	0.999	0.979	0.897	0.825	1.197	1.131	1.108	0.988	0.973	0.944
HP1	0.957	0.932	0.925	1.042	1.030	1.011	1.016	0.959	0.951	0.957	0.950	0.958
HP2	0.947	0.922	0.916	0.924	0.938	0.957	0.916	0.885	0.945	0.970	0.972	1.000
CF	0.947	0.921	0.905	1.104	1.094	1.061	0.962	0.936	0.945	0.948	0.945	0.968
HJ	0.953	0.926	0.908	0.982	0.988	1.049	1.000	0.963	0.966	1.013	1.025	1.035
MR	0.989	0.967	0.960	1.325	1.246	1.114	0.911	0.778	0.739	0.917	0.866	0.873
DSTN	0.946	0.897	0.877	0.938	0.976	0.957	1.000	0.846	0.798	1.029	1.023	0.985
Nb of forecast	26	24	22	26	24	22	26	24	22	26	24	22

Notes : the entries in italics show the RMSE of the AR forecast, other entries show the ratio of the RMSE of forecasts based on the method specified to the RMSE of the AR forecast. Hence, a ratio below unity denotes an improvement in forecast accuracy. QT = real rate corrected with quadratic trend, HP1 = HP (1,600) filtered IRG, HP2 = HP (26,500) filtered IRG, CF = Christiano-Fitzgerald (2003) filtered IRG, HJ = Harvey-Jaeger UC model, MR = baseline IRG using the UC model as in Mésonnier and Renne (2006), DSTN = first difference in the short term nominal rate of interest.

Table 6: predictive power of different measures of the real IRG for inflation, real activity and credit growth - Forecast sample: 1999Q1-2005Q4 – Iterated forecasts

Ratios of RMSE of competing bivariate models to RMSE of the benchmark AR model

Model	H=2	H=4	H=6	H=2	H=4	H=6	H=2	H=4	H=6	H=2	H=4	H=6
	Inflation			GDP growth			Unemployment			Credit growth		
AR	*0.969*	*0.939*	*0.955*	*1.290*	*1.165*	*1.025*	*3.863*	*4.476*	*4.984*	*1.210*	*1.308*	*1.482*
HJ quasi real time	1.001	0.997	0.996	0.920	0.959	0.973	0.960	0.964	1.006	0.999	1.005	1.012
MR quasi real time	0.986	0.979	0.979	1.507	1.664	1.884	1.058	1.117	1.181	1.030	1.103	1.127
QT	0.993	0.986	0.987	0.901	0.851	0.765	1.123	1.085	1.121	1.051	1.131	1.191
HP1	0.998	0.993	0.994	0.963	0.985	0.958	0.950	0.926	0.984	0.953	0.947	0.979
HP2	0.998	0.993	0.994	0.875	0.892	0.896	0.874	0.882	0.978	0.994	1.061	1.179
CF	1.001	0.995	0.995	1.005	1.045	1.011	0.906	0.920	0.987	0.943	0.920	0.940
HJ	1.002	0.997	0.997	0.919	0.959	0.974	0.962	0.964	1.005	0.999	1.005	1.011
MR	0.988	0.984	0.985	1.400	1.499	1.676	1.010	1.039	1.082	1.014	1.052	1.066
DSTN	1.003	1.015	1.013	1.013	1.014	1.029	0.984	0.968	0.974	0.986	0.975	0.979
Nb of forecast	26	24	22	26	24	22	26	24	22	26	24	22

Notes : the entries in italics show the RMSE of the AR forecast, other entries show the ratio of the RMSE of forecasts based on the method specified to the RMSE of the AR forecast. Hence, a ratio below unity denotes an improvement in forecast accuracy. Automatic lag selection using the AIC. QT = real rate corrected with quadratic trend, HP1 = HP (1,600) filtered IRG, HP2 = HP (26,500) filtered IRG, CF = Christiano-Fitzgerald (2003) filtered IRG, HJ = Harvey-Jaeger UC model, MR = baseline IRG using the UC model as in Mésonnier and Renne (2006), DSTN = first difference in the short term nominal rate of interest.

Chart 1: Alternative measures of the real interest rate gap for the euro area over the whole sample (1979-2005)

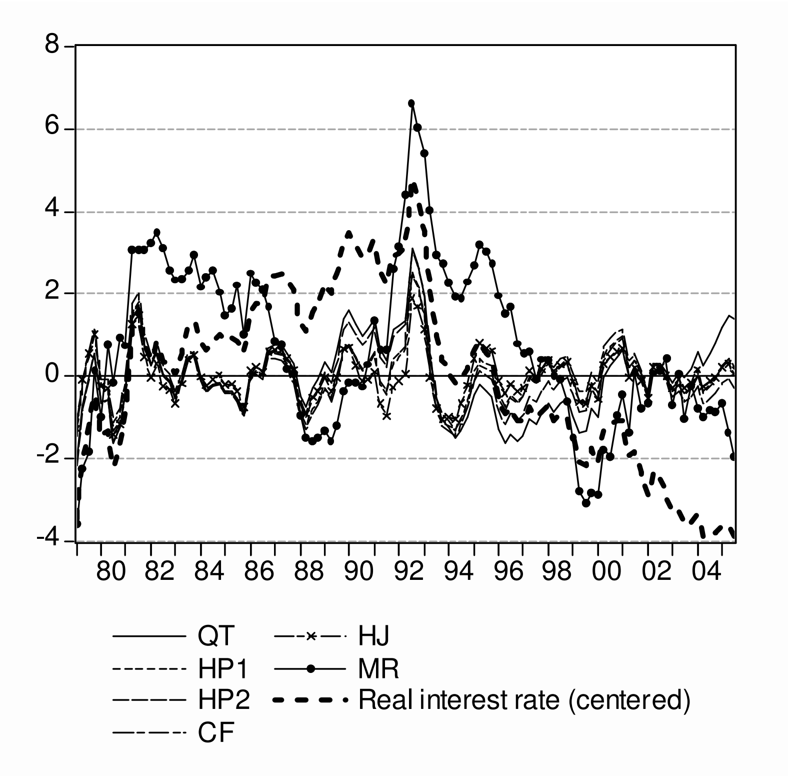
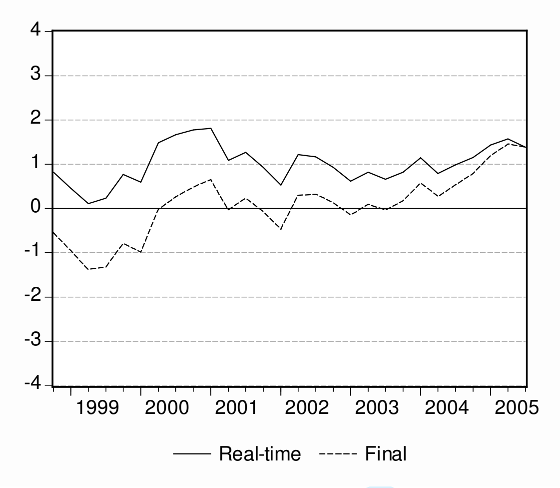
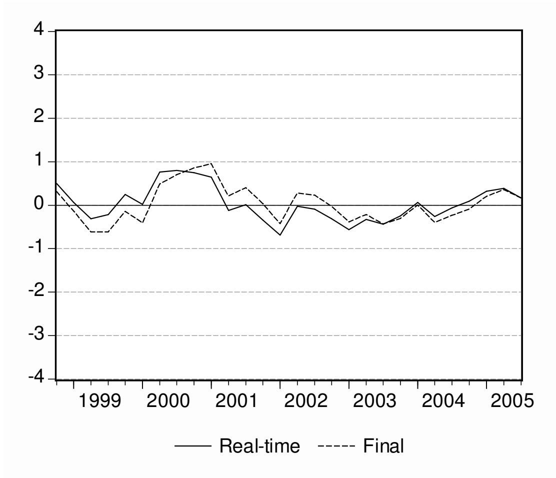


Chart 2: Quasi-real time and final end-of-sample estimates of the interest rate gap

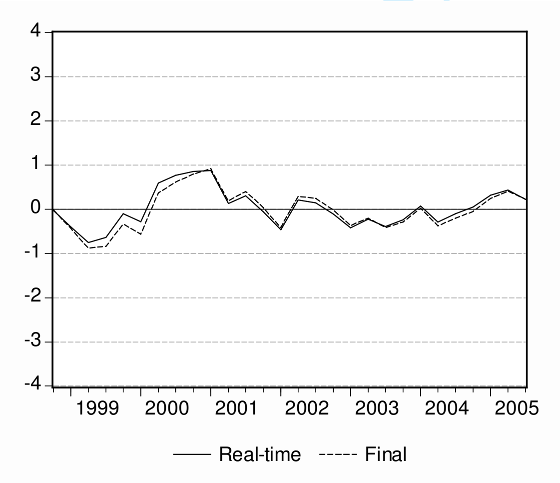
Quadratic trend



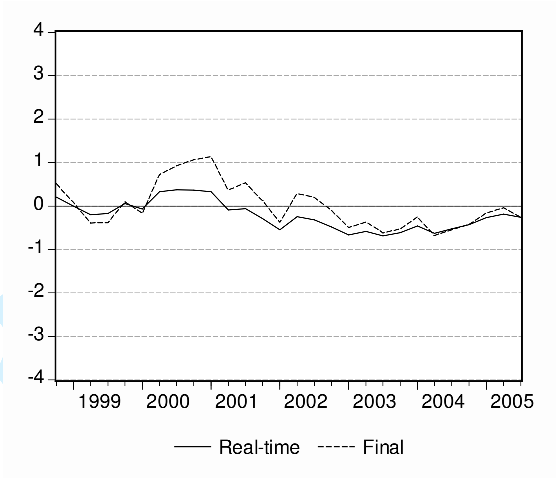
HP filter (lambda=1,600)



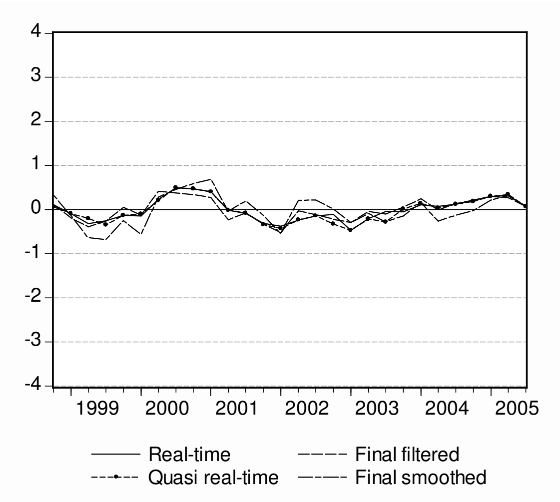
HP filter (lambda=26,500)



Christiano-Fitzgerald asymmetric band-pass filter



Harvey-Jaeger UC model



Mésonnier-Renne semi-structural UC model